CS190C Lec7

Hugging Face

Overview

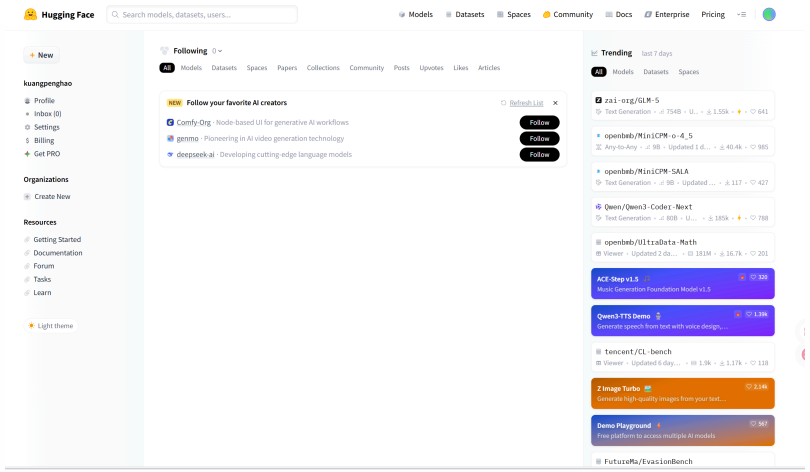
- HF Hub
- HF Libraries
  - Load a model: `transformers`
  - Prepare training data: `dataset`
  - Easily train a model: `Trainer`

PART1: HF Hub

What is huggingface?

Huggingface can be considered as `Github` of AI domain:

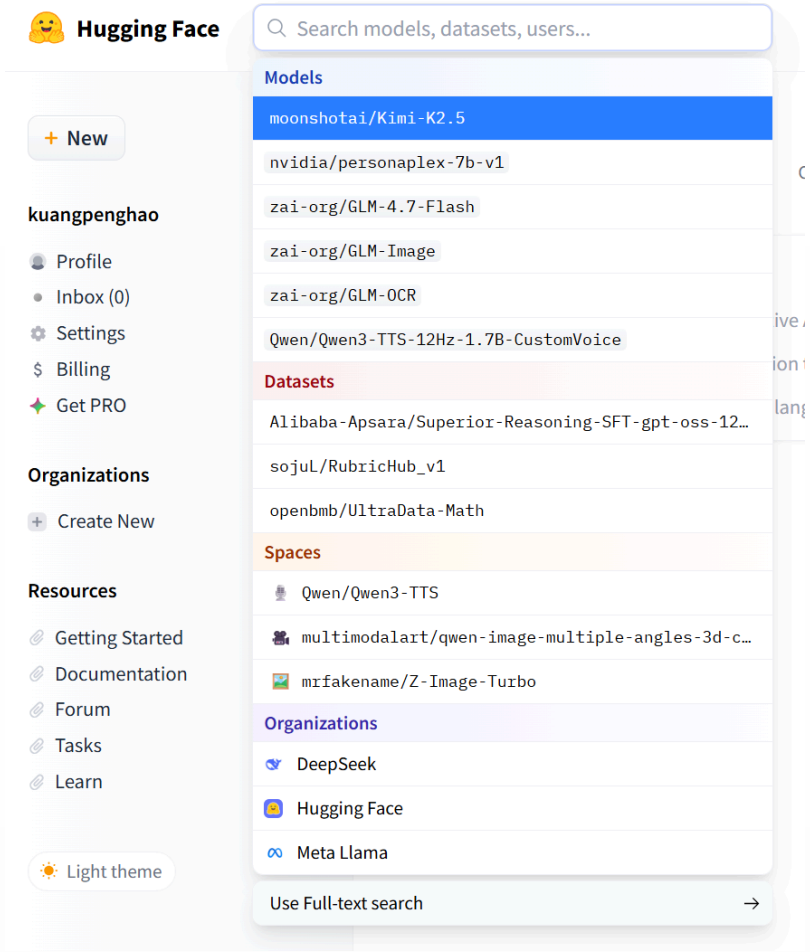
- You can browse a large number of models and datasets on the hub.
- You can download and upload models and datasets.
- Hugging face provide powerful library functions to help with it.



What is huggingface?

On huggingface hub, you can search on the homepage.

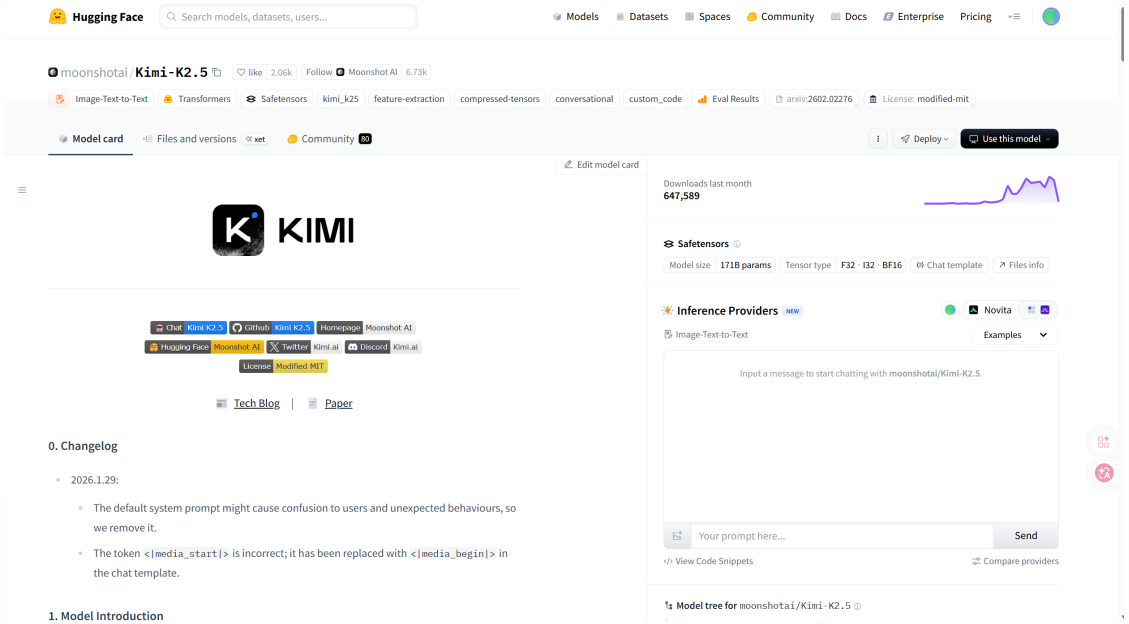
- Models
- Datasets
- Spaces
- Organizations



Models

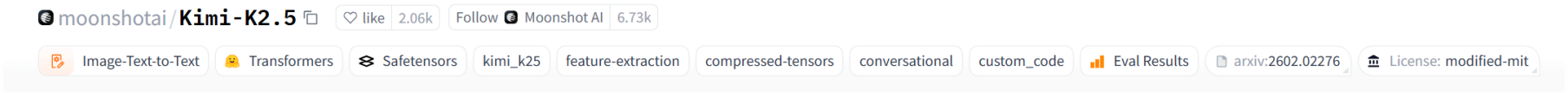
Trained models which can directly use to run tasks.

For example: https://huggingface.co/moonshotai/Kimi-K2.5

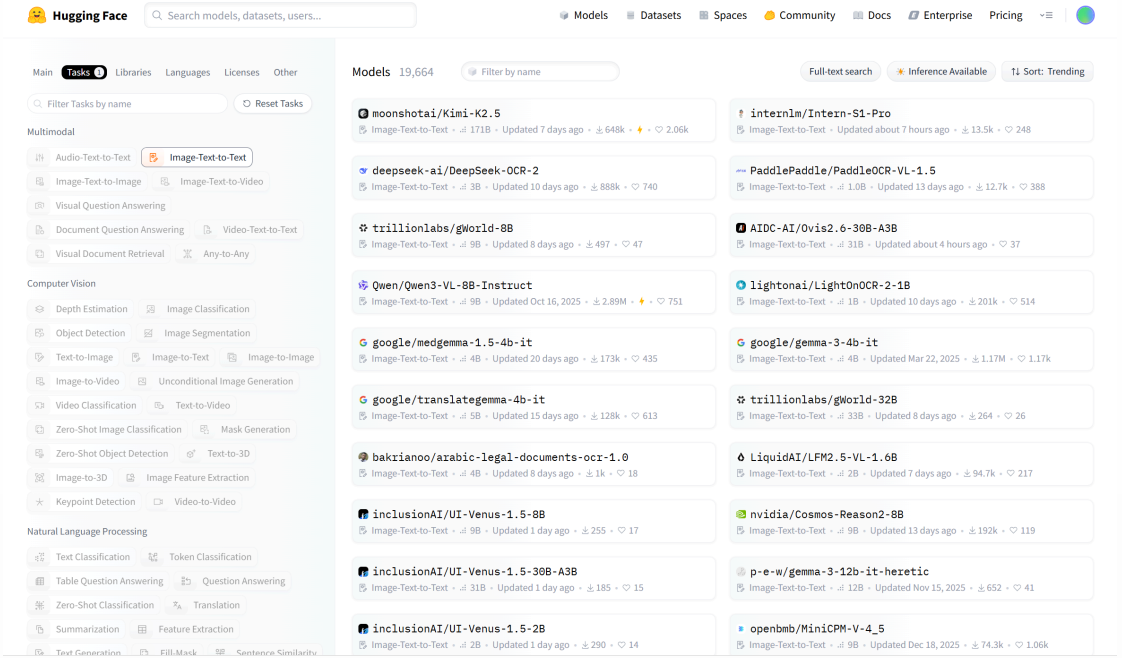


Models

What can we know about this model?



- Tasks: `Image-Text-to-text`. It is capable of multimodal task.
- Libraries: `Transformer` `Safetensors` and so on. The model is depend on these libraries.



Models

Refer to model card, we can find more informations of model. It is the same as `README.md` in github.

- Information of model
- Evaluation results
- Usage of model

2. Model Summary

Architecture	Mixture-of-Experts (MoE)
Total Parameters	1T
Activated Parameters	32B
Number of Layers (Dense layer included)	61
Number of Dense Layers	1
Attention Hidden Dimension	7168
MoE Hidden Dimension (per Expert)	2048
Number of Attention Heads	64
Number of Experts	384
Selected Experts per Token	8
Number of Shared Experts	1
Vocabulary Size	160K
Context Length	256K
Attention Mechanism	MLA
Activation Function	SwiGLU
Vision Encoder	MoonViT
Parameters of Vision Encoder	400M

6. Model Usage

The usage demos below demonstrate how to call our official API.

For third-party APIs deployed with vLLM or SGLang, please note that:

> - Chat with video content is an experimental feature and is only supported in our official API for now.
> - The recommended `temperature` will be `1.0` for Thinking mode and `0.6` for Instant mode.
> - The recommended `top_p` is `0.95`.
> - To use instant mode, you need to pass `{'chat_template_kwargs': {"thinking": False}}` in `extra_body`.

Chat Completion

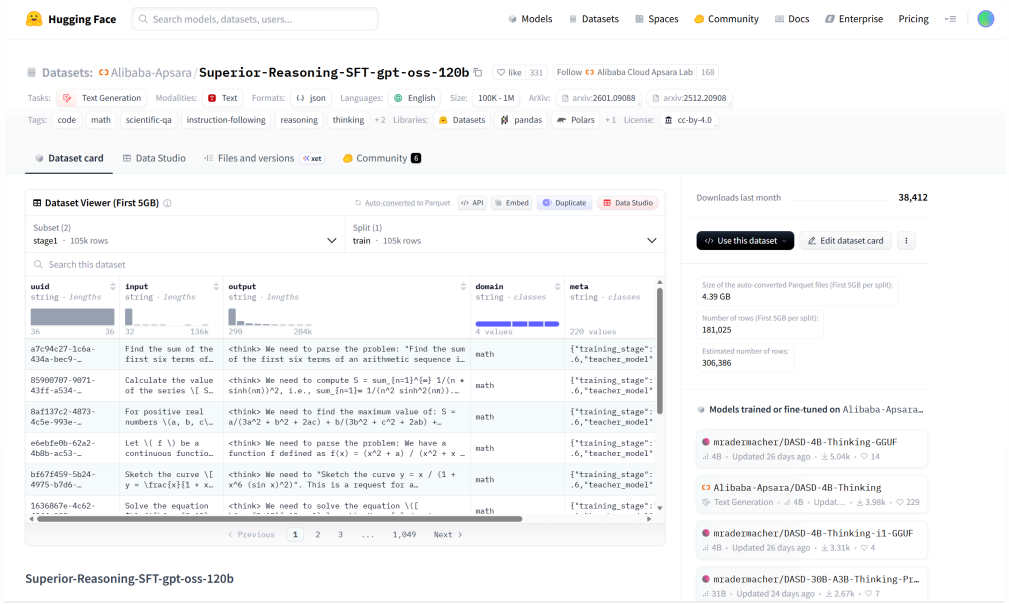
This is a simple chat completion script which shows how to call K2.5 API in Thinking and Instant modes.

```
import openai
import base64
import requests
def simple_chat(client: openai.OpenAI, model_name: str):
    messages = [
        {'role': 'system', 'content': 'You are Kimi, an AI assistant created by M
        {
            'role': 'user',
            'content': [
                {'type': 'text', 'text': 'which one is bigger, 9.11 or 9.9? think
            ],
        },
    ]
    response = client.chat.completions.create(
```

Datasets

Datasets which can directly use to train model.

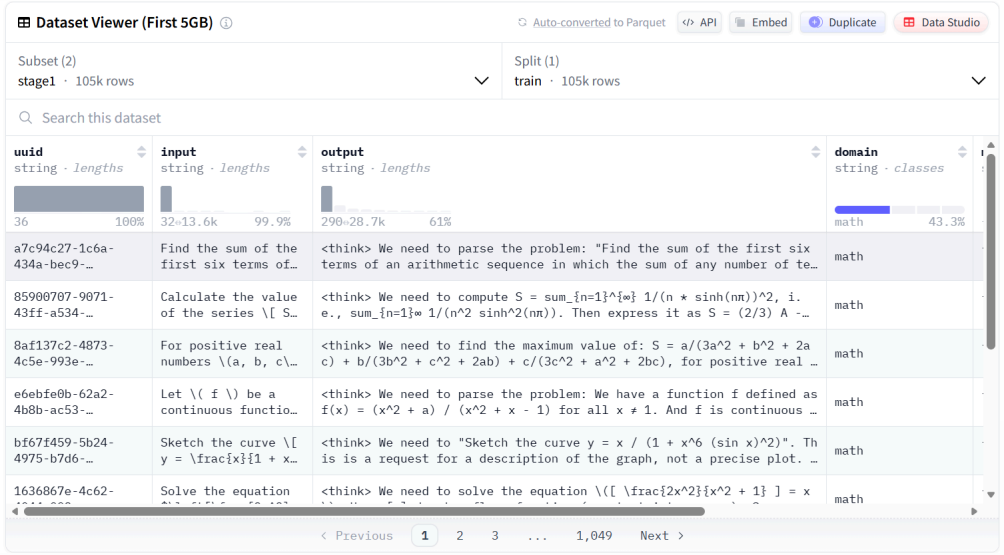
For example: https://huggingface.co/datasets/Alibaba-Apsara/Superior-Reasoning-SFT-gpt-oss-120b



Datasets

Also, we can browse information, such as data, number of samples, size on model card page.

For example, we can get most information through Dataset Viewer.



Spaces

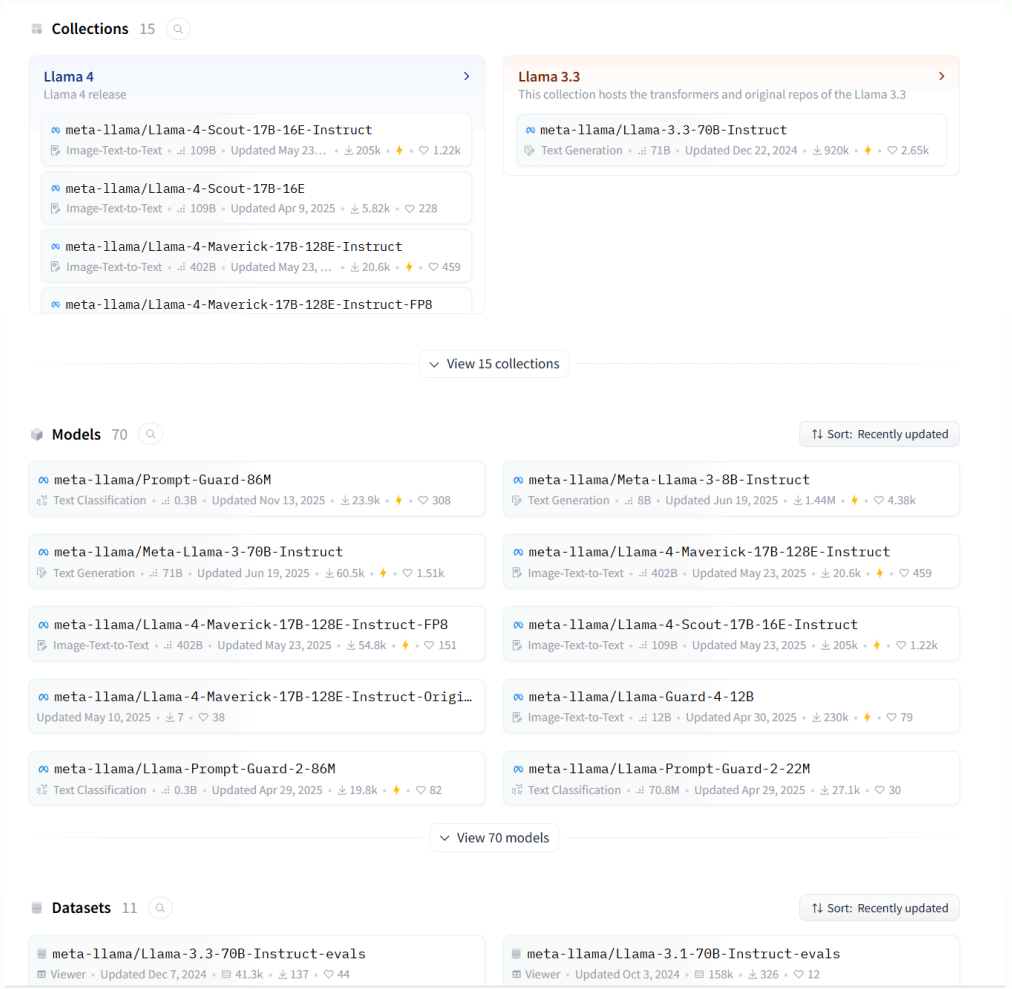
Some web applications based on trained model. You can visit and experience it.

For example: https://huggingface.co/spaces/mrfakename/Z-Image-Turbo

Organizations

Information, models, datasets of an organization.

For example: https://huggingface.co/meta-llama



In a word, we can browse all kinds of models and datasets on hugging face.

But how can we actually get access and make use of them?

We need libraries provided by hugging face.

PART2: HF Libraries

PART2.1: Load a model: `transformers`

How to load a trained model?

What's the premise of succefully running a trained model?

- Model architecture and model task.
  - For example, model `bert-base-uncased`, running masked language modeling task.
- Config of model.
  - Number of layers, hidden size, vocabulary size and so on.
- Tokenizer of model.
- Finally, trained parameters.

How to load a trained model?

Hugging face library `transformers` provides multiple `Auto` libraries, covering all operations above.

- `AutoConfig`
- `AutoTokenizer`
- `AutoModel` `AutoModelForCausalLM` `AutoModelForSequenceClassification` and so on

Libraries and model-id

```
import torch
from transformers import AutoTokenizer, AutoModelForMaskedLM, AutoConfig

model_id = "bert-base-uncased"
```

This means:

- We will use model `bert-base-uncased` to run our language task.
- The language task to be run is `MaskedLM`

Config

```
config = AutoConfig.from_pretrained(model_id)
```

We use `AutoConfig` to load configuration of this model. But how does it works?

- Check if `model_id` a local path. If it is, directly load this `json` configuration file.
- Check if `model_id` a local cached path then (The default path is `~/.cache/huggingface/`).
- Finally, send a request to huggingface to download `json` file to local directory.

Config


```
{
  "architectures": [
    "BertForMaskedLM"
  ],
  "attention_probs_dropout_prob": 0.1,
  "directionality": "bidi",
  "hidden_act": "gelu",
  "hidden_dropout_prob": 0.1,
  "hidden_size": 768,
  "initializer_range": 0.02,
  "intermediate_size": 3072,
  "layer_norm_eps": 1e-12,
  "max_position_embeddings": 512,
  "model_type": "bert",
  "num_attention_heads": 12,
  "num_hidden_layers": 12,
  "pad_token_id": 0,
  "pooler_fc_size": 768,
  "pooler_num_attention_heads": 12,
  "pooler_num_fc_layers": 3,
  "pooler_size_per_head": 128,
  "pooler_type": "first_token_transform",
  "type_vocab_size": 2,
  "vocab_size": 21128
}
```


- For `model_type`:
  - It decides which kind of operation logic should be followed.
- For `architectures`:
  - It decides task of language model and parameter architecture of task head.
- For other items:
  - It decides common configuration of model.

Config

- `model_type`: `bert` here corresponds to the code logic of `transformers.models.bert`, which can be found in https://github.com/huggingface/transformers/blob/main/src/transformers/models/bert/configuration_bert.py
  - `configuration_bert.py`: How to fill the raw decoded dictionary of `config.json` with default values, and instantiate it with `class BertConfig`.

Config

- `architectures`: `BertForMaskedLM` here, corresponds to a bert model with a mask filling head.
  - If we use `AutoModelForMaskedLM`, parameters will be perfectly loaded.
  - If we use `AutoModel` (just load raw model without any head), parameters of mask filling head will be ignored.
  - If we use `AutoModelForSequenceClassification`, the missing classification head parameters will be randomly initialized.

Tokenization

```
tokenizer = AutoTokenizer.from_pretrained(model_id)
```

Define tokenizer. Also obey the order of retrieving.

- First, decide which kind of tokenizer should be used (`BertTokenizer` here).
- Load the tokenization logic, which can be found in https://github.com/huggingface/transformers/blob/main/src/transformers/models/bert/tokenization_bert.py, and instantiate the tokenizer.

Model

```
model = AutoModelForMaskedLM.from_pretrained(
    model_id,
    config=config
)
```

- Load model. As discussed before, it may throw a warning of random initialization of task head if we use `AutoModelForSequenceClassification`. If we use `AutoModelForMaskedLM`, it will be fine.
- https://github.com/huggingface/transformers/blob/main/src/transformers/models/bert/modeling_bert.py
- Till now, all parameters have loaded (except task head if we use `AutoModelForSequenceClassification`) with trained parameters. So what has class `AutoModel` done?

Model

It can be separated as several steps:

- Configuration. `config = AutoConfig.from_pretrained("bert-base-uncased")`
  - If we have explicitly configured, it can be ignored.
- Choose model class (`BertForMaskedLM`) and instantiate the random initialized model.
- Download `pytorch_model.bin` / `model.safetensors` file containing trained parameters
- Load parameters.

Inference

```
import torch
from transformers import AutoTokenizer, AutoModelForMaskedLM, AutoConfig

model_id = "bert-base-uncased"
config = AutoConfig.from_pretrained(model_id)
tokenizer = AutoTokenizer.from_pretrained(model_id)

text = "这家餐厅味道真不错！"
inputs = tokenizer(text, return_tensors="pt")

with torch.no_grad():
    outputs = model(**inputs)

logits = outputs.logits
probabilities = torch.nn.functional.softmax(logits, dim=-1)
predicted_class_id = torch.argmax(probabilities, dim=-1).item()
print(f"Predicted ID: {predicted_class_id}")
```

However, if we want to actually train a model from scratch, we should need more libraries.

- `transformers` for model preparation
- `dataset` for data preparation
- `Trainer` for training arrangement

PART2.2: Prepare training data: `dataset`

Suppose we are using dataset `iohadrubin/wikitext-103-raw-v1` to train a masked language model `"bert-base-uncased"`. How should we process the data?

- Load the original dataset
- Tokenization
- Grouping and trunking
- Dynamic masking
- Serving data

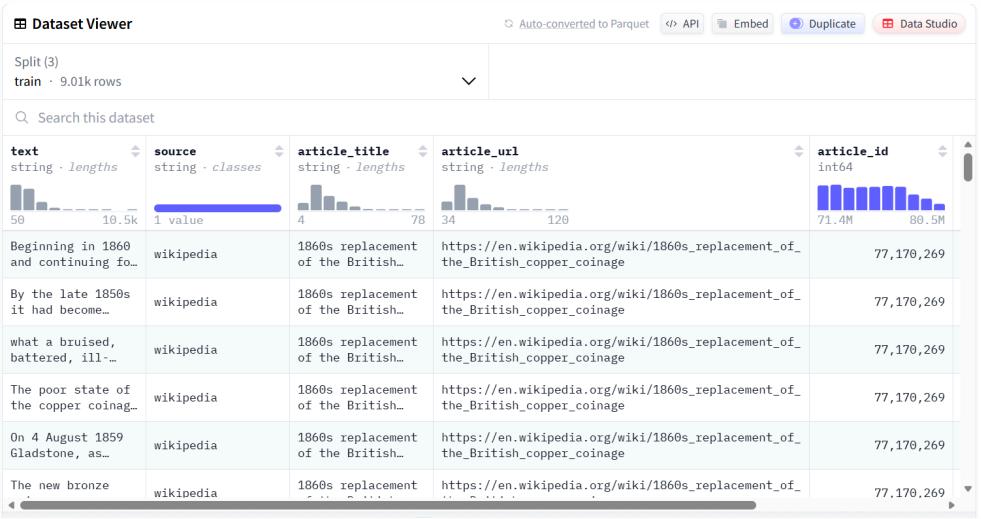
Loading

```
from datasets import load_dataset
dataset = load_dataset("iohadrubin/wikitext-103-raw-v1")
```

But what's the basic structure of the object `dataset`?

We may observe a more complex dataset example `vesteinn/wikitext-220728-250728` first.

Structure of dataset



- `dataset` is a dictionary with three keys: `train`, `validation`, `test`, just like 3 tables.
- Each table has columns `text`, `source` and so on, each column is a list.
- Each table has multiple rows, each row is a dictionary with keys `text`, `source` and so on.
- So a table can be called by `dataset["train"]`, a column can be called by `dataset["train"]["source"]`, a row can be called by `dataset["train"][0]`.

Tokenization

```
def tokenize_function(examples):
    # Tokenize data of column "text", and also return special tokens mask.
    return tokenizer(examples["text"], return_special_tokens_mask=True)

# Use tokenize_function to run tokenization, process batch data parallely, use 4 CPU process.
# When finish processing, remove column "text".
tokenized_datasets = dataset.map(
    tokenize_function,
    batched=True,
    num_proc=4,
    remove_columns=["text"]
)
```

Processed 'tokenized_datasets' is like:

```
{
  "input_ids": [[101, 791, 1921, 4685, 7231, 102], [101, 2769, 4638, 6821, 2769, 102]],
  "special_tokens_mask": [[1, 0, 0, 0, 0, 1], [1, 0, 0, 0, 0, 1]]
}
```

Grouping & Chunking

The length of setences are different. For simplicity, we directly grouping tokens of all tokenized sentences into a long string, and directly chunk them to `seq_len` blocks.

```
block_size = 128
def group_texts(examples):
    concatenated_examples = {k: list(chain(*examples[k])) for k in examples.keys()} ## directly concat tokens into a long string
    total_length = len(concatenated_examples[list(examples.keys())[0]]) ## get length of the long string
    if total_length >= block_size:
        total_length = (total_length // block_size) * block_size  ## discard tail of the string

    result = {
        k: [t[i : i + block_size] for i in range(0, total_length, block_size)]
        for k, t in concatenated_examples.items()
    } ## k is the key and t is the value (the long string, which is a list). For each list, chunk it into multiple blocks  and return.
    return result

lm_datasets = tokenized_datasets.map(
    group_texts,
    batched=True,
    num_proc=4,
) ## The grouped and chunked dataset
```

Dynamic masking

For BERT, actually we should do masking, but when?

If we do masking during `dataset.map` process (that is: implementing masking logic in tokenize_function), the model will receive static masking task, which is more possible to overfit.

So we do dynamic masking, which needs `DataCollatorForLanguageModeling` library in `transformers`

Dynamic masking

Instantiate a data_collator function with masking probability 15%.

```
from transformers import DataCollatorForLanguageModeling

data_collator = DataCollatorForLanguageModeling(
    tokenizer=tokenizer,
    mlm=True,
    mlm_probability=0.15
)
```

And then, we are readied to train the language model with prepared `lm_datasets` and `data_collator`

PART2.3: Easily train a model: `Trainer`

Things we should prepare for training is almost the same as discussed in Lec6.

- Training arguments
- Instantiated model
- Processed data
- Trainer

Training arguments

For simplicity, we can define in python script, but we also recomment to define in a bash script.

```
from transformers import TrainingArguments

batch_size = 16

training_args = TrainingArguments(
    output_dir="./bert-wikitext2-mlm",
    overwrite_output_dir=True,

    # core arguments
    num_train_epochs=3,
    learning_rate=2e-5,
    weight_decay=0.01,
    per_device_train_batch_size=batch_size,
    per_device_eval_batch_size=batch_size,
```

```
    # strategies of evaluation and saving
    evaluation_strategy="epoch",
    save_strategy="epoch",
    load_best_model_at_end=True,

    fp16=True,

    # strategies of logging
    logging_steps=100,
    report_to="none",
)
```

Instantiated model

We've prepared the model before?

```
model = AutoModelForMaskedLM.from_pretrained(
    model_id,
    config=config
)
```

But it is the pre-trained model, and we should load model with parameters just randomly initialized!

Instantiated model

We've prepared config before:

```
config = AutoConfig.from_pretrained(model_id)
```

And we use `from_config` method to instantiate the model!

```
model = AutoModelForMaskedLM.from_config(config)
```

Trainer

```
from transformers import Trainer

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=lm_datasets["train"], # training data
    eval_dataset=lm_datasets["validation"], # evaluation data
    tokenizer=tokenizer, # we also save tokenizer in checkpoint
    data_collator=data_collator, # use data_collator to dynamically mask sentence
)
```

```
trainer.train()
eval_results = trainer.evaluate()
trainer.save_model("./final_bert_wikitext103")
```

Official training scripts

We can directly get training scripts for training tasks like `CausalLM`, `MaskedLM` and so on provided by huggingface: https://github.com/huggingface/transformers/tree/main/examples/pytorch/language-modeling

These scripts has extremly strong function like training from scratch, fine-tuning, start training from checkpoint and distributed training.

We usually use them during daily research and industrial production.